High Accuracy Classification of Myopathy and Normal Electromyography Signals Using ResNet50 Neural Network

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Introduction

Myopathies are skeletal muscle disorders that involve chronic (long-standing) muscle inflammation, muscle weakness, and, in some cases, muscle pain, primarily due to dysfunction of muscle fiber [14]. Most myopathies fall under two main categories: acquired and inherited [15]. Myopathies are usually diagnosed using a variety of techniques, such as laboratory tests, genetic tests, and muscle biopsies [15].

One of the easiest and most effective ways for diagnosing myopathies in conjunction with other tests is electromyography (EMG) [15]. An EMG has two parts: a nerve conduction study and a needle EMG. In a needle EMG, a needle electrode is directly inserted into the patient's muscle to record the electrical signals motor neurons transmit, which cause muscles to contract [7]. The electrodes on the needle translate these signals into graphs or numerical values that are then interpreted by a specialist [7]. To read an EMG signal, a specialist must carefully analyze the signal, which could delay the test results by a few days [7]. Furthermore, the accuracy of the EMG results, by nature, is dependent upon the specialist's analysis, which may differ from person to person [7].

Imaging diagnostics, which includes EMG analysis, have estimates of average diagnostic error rates ranging from 3% to 5%, leading to approximately 40 million diagnostic errors annually worldwide [9]. In contrast, an automated diagnosis of normal and myopathy EMG signals could be more accurate than these current diagnosis rates, or at least provide a data-driven second opinion for the specialist. In addition, an automated diagnosis would yield real-time results after the tests are conducted. Thus, an automated diagnosis with high accuracy

that yields immediate results would save the medical imaging industry valuable time and resources.

With improvements in deep learning technology and availability of datasets, automated and instant diagnosis of these signals is becoming a possibility. Various methods of automated diagnosis have been tried and tested before; they involve distinguishing between some combination of neuropathic, myopathy, and normal EMG signals [6, 10, 18, 23]. For example, in a 2007 study, time domain and wavelet decomposition using continuous wavelet transformation were explored for discrimination of neuropathic, myopathy, and normal EMG signals [10]. The highest accuracy between myopathy and normal signals was 73.33% using SVM classification [10]. In 2006, a study used a wavelet neural network using AR (autoregressive model) method for EMG representation to obtain a 90% accuracy distinguishing between myopathy and normal EMG signals [23]. In 2014, a study used mel-frequency cepstral coefficient (MFCC) on motor unit action potentials (MUAPS) extracted from EMG decomposition to distinguish between neuromuscular and normal signals [6]. The highest accuracy reached in this 2014 study was 92.5% [6]. A study in 2013 obtained a 96.75% accuracy using a BP neural network to distinguish using Singular Value Decomposition EMG signals [18]. However, the study only used 40 EMG signals in total), which was one of the limitations of the study (see Discussion) [18].

A study published in 2017 distinguishing between Amyotrophic Lateral Sclerosis (ALS) and normal EMG signals obtained a 96.80% accuracy, which was higher than the previous myopathy and normal EMG signal studies [22]. The study's methodology involved converting the EMG signals into time frequency representations, which had rich texture information that

could be extracted by deep learning, and using these images to train a reinforcement learning convolutional neural network [22].

A similar methodology could be used to distinguish between myopathy and normal EMG signals to obtain a similarly high accuracy. If time frequency representations, such as a spectrogram, can also allow a neural network to distinguish between normal and myopathy EMG signals with a high accuracy, it would confirm the value in performing analyzing time frequency representations of the images. Furthermore, because publicly available myopathy and normal EMG signals are not common, the use of a neural network using transfer learning could potentially help to achieve a greater accuracy. Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task [4]. This saves time and can increase network accuracy with its initial features and weights [4]. Thus, it is hypothesized that after a transfer neural network is trained on time frequency representations of EMG signals, such as spectrogram and scalogram representations, the neural network will be able to accurately (90%+) distinguish between normal and myopathy EMG signals.

Creating a neural network trained on time frequency representations of EMG signals with a high accuracy would be a significant accomplishment that would provide a new way of accurately classifying between myopathy and normal EMG signals. This innovation provides further evidence demonstrating that deep learning is a viable and promising technique in medical diagnosis.

Materials and Methods

A schematic flow chart of the methodology used in this research is shown in Figure 1. The EMG signals undergo spectrogram and scalogram time frequency transformations. These images were then fed into a neural network where the network's convolutional blocks extracted features that the network's fully connected layers classified as either myopathy or normal. The subsequent sections describe the software and the methodology used in this study.

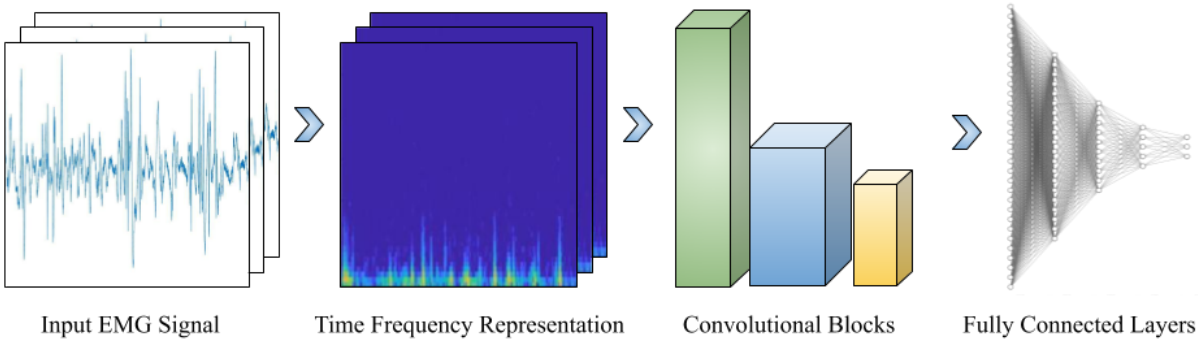


Figure 1. Overview of methods used in investigation (Swartwood, 2020)

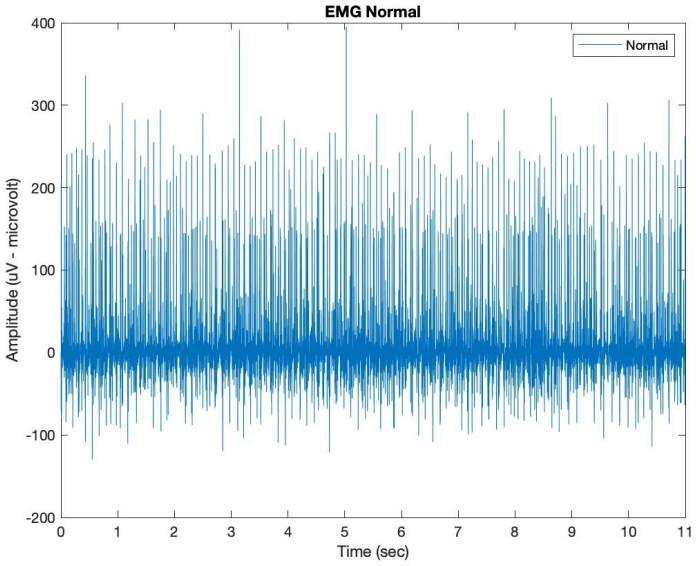
EMG Signals

EMG signals, containing both the normal and myopathy signals, were collected from the University of Copenhagen in 2001 [17]. The control group consisted of normal subjects (n = 10) aged 21-37 years. The group with myopathy consisted of 7 patients aged 19-63 years. Multiple scans were taken from each patient using a standard concentric needle electrode. The sampling rate of EMG signals was almost 24 kHz and digitized by A/D convertor of 16-bit resolution. The signals were filtered at 2 Hz and 10 kHz by high- and low-pass filters, respectively. In this study, myopathy (n = 107) and normal signals (n = 106) from the brachial biceps of these patients were

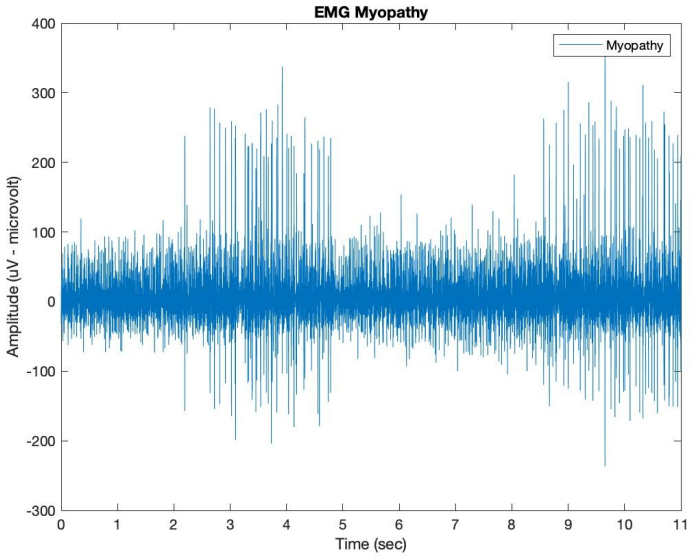
used. The signals were obtained from Emglab [16] , a program built for EMG decomposition, which had the signals openly on its website (http://www.emglab.net/emglab/Signals/N2001/index.html).

Image Preprocessing

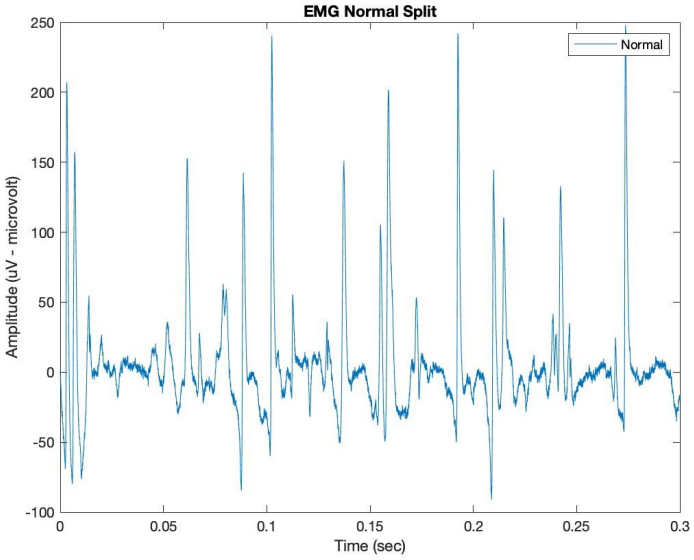
The EMG signals were accessed from Emglab and imported to Matlab using Emglab software. Matlab and PyCharm were the coding platforms used in this investigation. Raw EMG signals from patients can be seen in Figure 2. Using Matlab, a script was created that split each EMG signal into 35 separate parts (7,500 samples each). Each part was converted and saved into a spectrogram and scalogram image, which is shown in Figure 3.

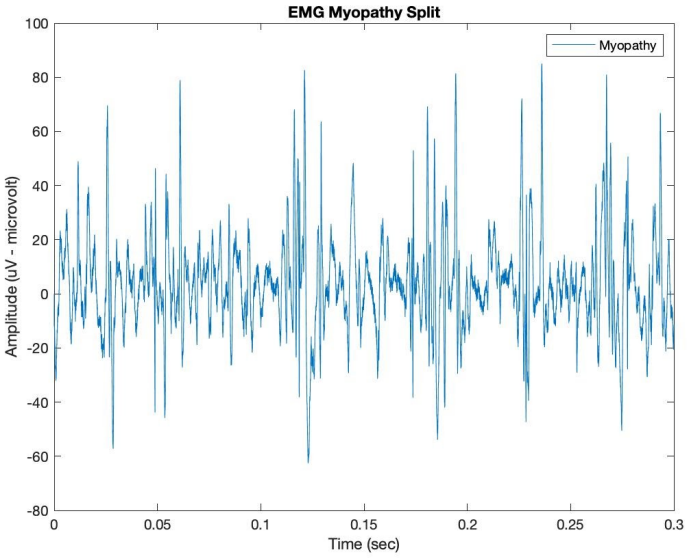


A



B

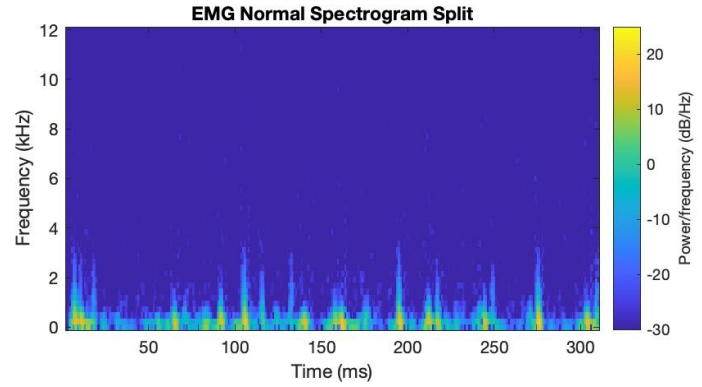




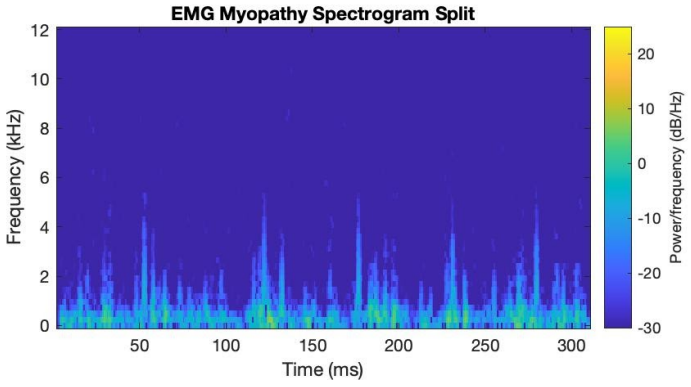
C **D**

Figure 2. Visual representations of normal (2A and 2C) and myopathy (2B and 2D) EMG signals (Swartwood, 2020)

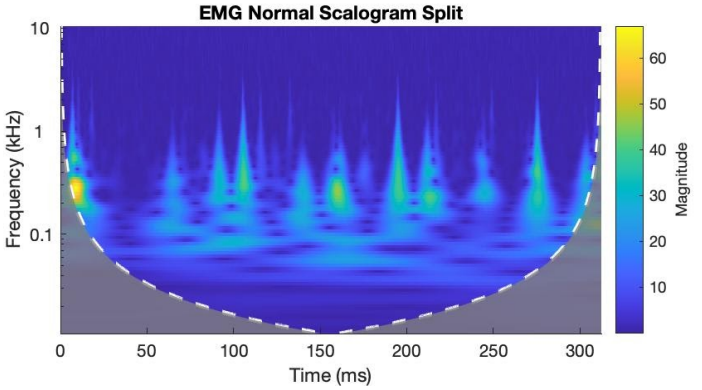
A spectrogram displays signal strength over time at the various frequencies present in a waveform [26]. For spectrogram representation, the windowing operation was performed with a Hamming window with length of 100. The number of overlaps between adjoining segments was chosen as 80 and the number of sampling for Fourier Transform was selected as 100. A scalogram is the absolute value of the continuous wavelet transform (CWT) of a signal, plotted as a function of time and frequency [21]. For the scalogram, the analytic Morse wavelet with a symmetry parameter of 3 was used and a time-bandwidth product of 60 was chosen. The scalogram used 10 voices per octave. Scalogram and spectrogram were the chosen time frequency representations because of their proven ability to analyze wave signals well [3].



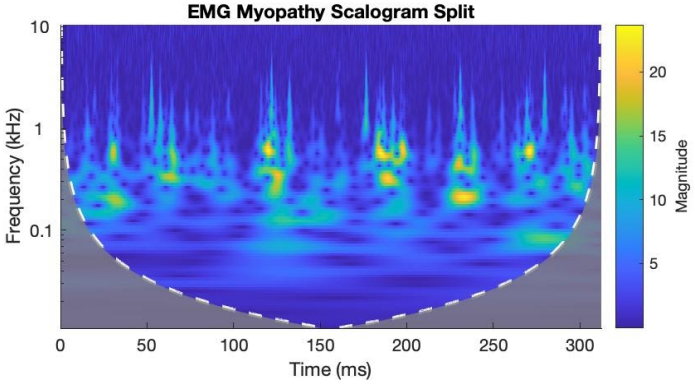
A



B



C



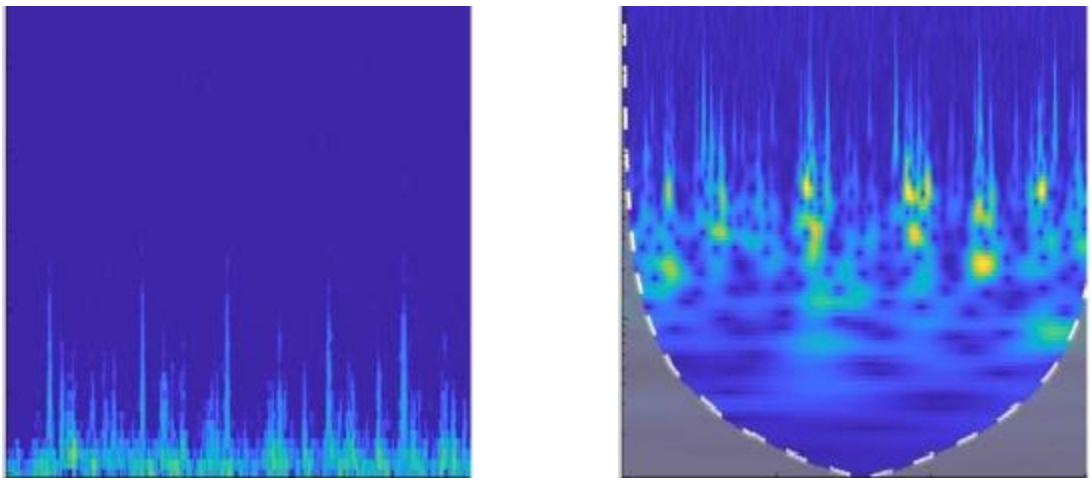
D

Figure 3. Spectrogram (3A and 3B) and scalogram (3C and 3D) representations of EMG signals (Swartwood, 2020)

After the separation of the EMG signals, there were normal (N = 3,710) and myopathy (N = 3,745) EMG spectrogram and scalogram images each. Using Pycharm, a script was made that reorganized the EMG samples into different directories. The spectrogram and scalogram images, both in seperate folders, were each divided into subfolders. 70% of the images were moved to the train folder, 20% to the validation folder, and 10% to the test folder. This was performed to organize the data for the neural network. After being moved, the images were then cropped to

remove unnecessary space on the images, which is essential for network detection so only distinguishable image features are left. These fully processed images can be seen in Figure 4.

Assembling and Forming the Networks



A **B**

Figure 4. Examples of fully preprocessed spectrogram (4A) and scalogram (4B) representations of a myopathy EMG signal that were fed into the neural networks (Swartwood, 2020)

The scalogram and spectrogram images were then separately fed into different feed-forward neural networks with the same architecture. Image augmentation in the form of only horizontal reflections was used to increase the training data. This is important because it increases the pool of available data which allows the neural network to generalize better to obtain a higher accuracy on test data [4].

The network architecture was structured after a 3 block VGG model [4], and was built in PyCharm. Each block had a 2D convolution layer with Rectified linear activation function (Relu)

activation; padding; and 32, 64, and 128 (3x3) filters, respectively. This was followed by a max pooling layer (2x2 block), and a dropout (20%) layer for each block. Dropout layers randomly deactivate some neurons, which forces other neurons to learn more accurately. This is essential for the network to reduce overfitting, which is when the model memorizes the data instead of generalizing features from it. The blocks were followed by 5 fully connected layers, with a dropout layer (50%) between the first two fully connected layers. Relu activation was used except for the last fully connected layer, which used sigmoid activation. The model was trained for 100 epochs.

The images were also fed into transfer learning neural networks. The prepared images were fed into a pretrained VGG16 model [4, 24] in Pycharm and a pretrained ResNet50 model in matlab [20]. Both pretrained networks were trained to recognize 1000 classes on the ImageNet database [20, 24]. The fully connected layers of the VGG16 model were replaced with a flatten layer and 5 fully connected layers with dropout layers (20%) between the first, second, and third fully connected layers. For the pretrained ResNet50 neural network, the final fully connected layer and classification model was replaced with ones with two outputs and higher learning weights. The number of epochs was set to 25.

All models used the binary cross-entropy loss function (Figure 5) as well as the Adam Stochastic Gradient Descent Algorithm to evaluate the accuracy of the neural network in classifying myopathy and normal images. Adam was chosen as the optimizer because of its proven ability to outperform other optimiers (Figure 6). The accuracy and loss were the main factors that determined the network performance.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Figure 5. The binary cross entropy loss function used in the tested neural networks. The networks calculate the loss by computing the following sum, where y is the label and p(y) is the predicted probability of the point being 1 for all *N* points [4].

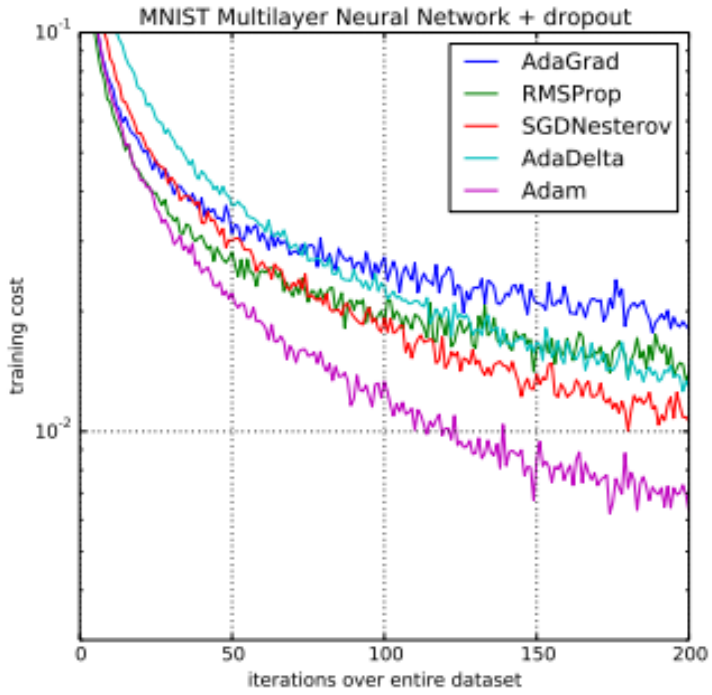


Figure 6. Adam combines two extensions of classical gradient descent: Adaptive Gradient Algorithm and Root Square Mean Propagation [4]. In this investigation, the standard values for the adam configuration parameters were utilized. These values were:lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0 [4].

Results

Of the normal (N = 3,710) and myopathy (N = 3,745) EMG spectrogram and scalogram images each, the neural network was validated on 640 normal images and 683 myopathy images and tested on 311 normal images and 325 myopathy images. The rest was used for training. Table 1 summarizes the validation and test accuracies of each neural network.

Table 1. Accuracies of the tested networks (Swartwood, 2020)

Neural Network	T–F method	Validation Accuracy (%)	Test Accuracy (%)
ResNet50 Transfer	Spectrogram	97.05	96.57
ResNet50 Transfer	Scalogram	96.44	96.55
VGG3	Spectrogram	94.32	94.97
VGG16 Transfer	Spectrogram	93.34	93.08
VGG16 Transfer	Scalogram	90.17	92.30
VGG3	Scalogram	87.75	88.36

The following graphs in Figures 7, 8, and 9 depict the accuracy, loss, and confusion matrix of the networks. This investigation's accuracy was then compared to other studies' accuracies in Table 2.

Figure 7.1 VGG3 Spectrogram

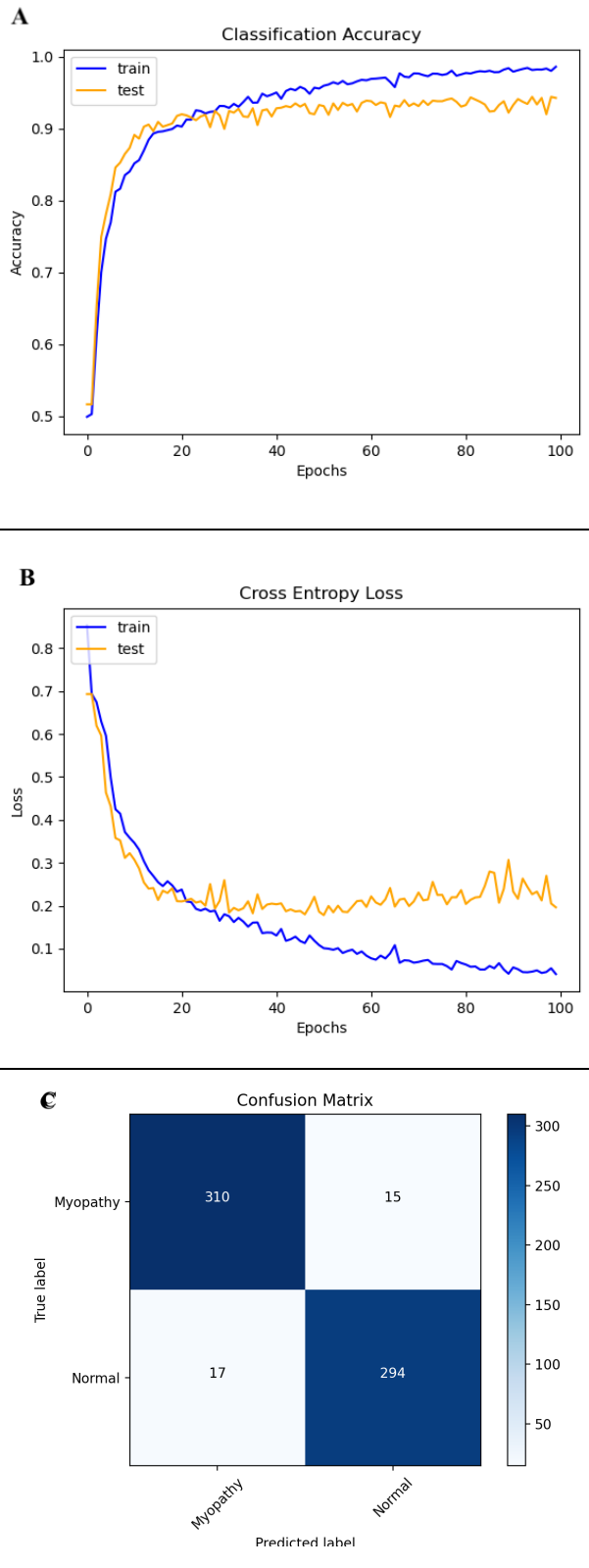


Figure 7.2 VGG3 Scalogram

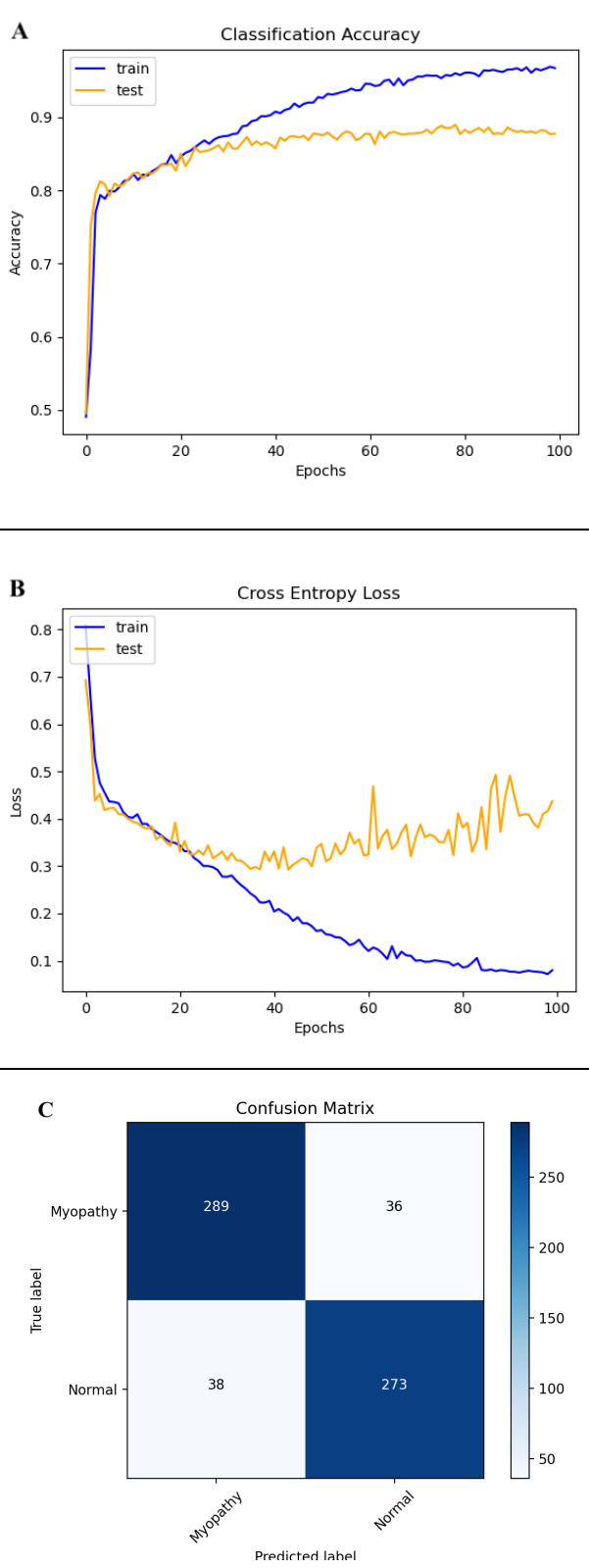
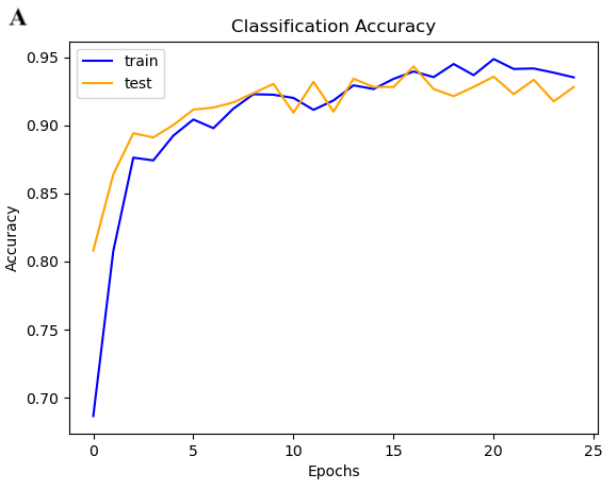
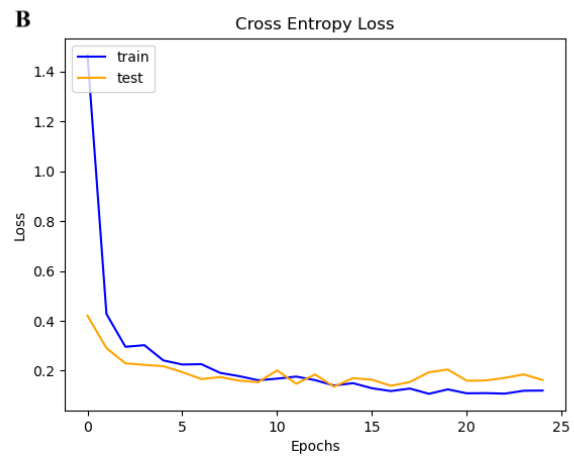


Figure 8.1 Transfer VGG16 Spectrogram





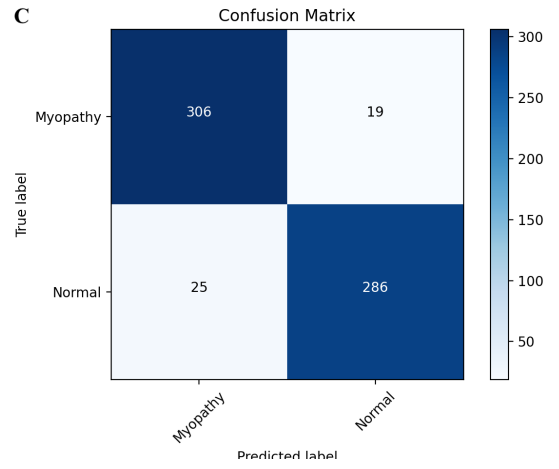
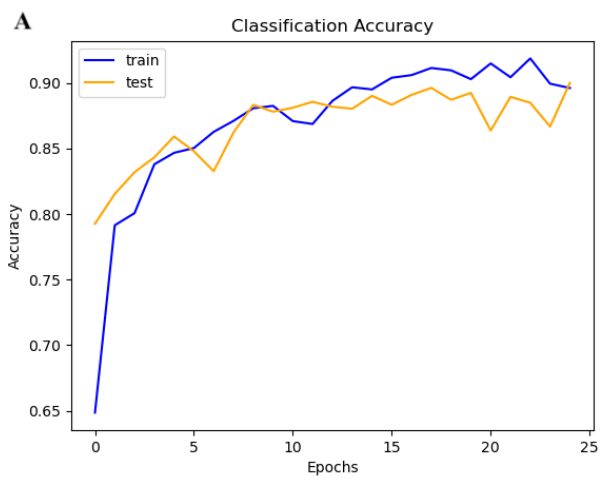
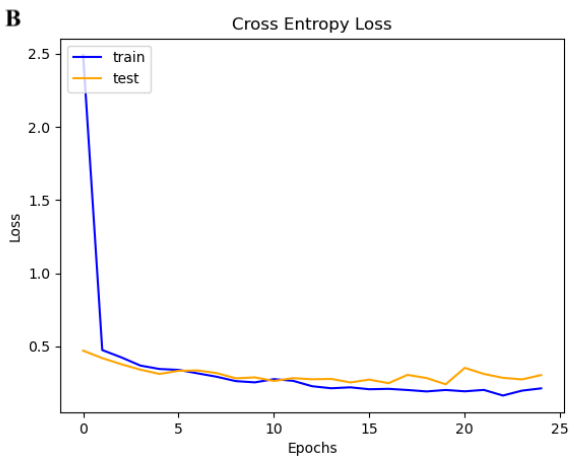


Figure 8.2 Transfer VGG16 Scalogram





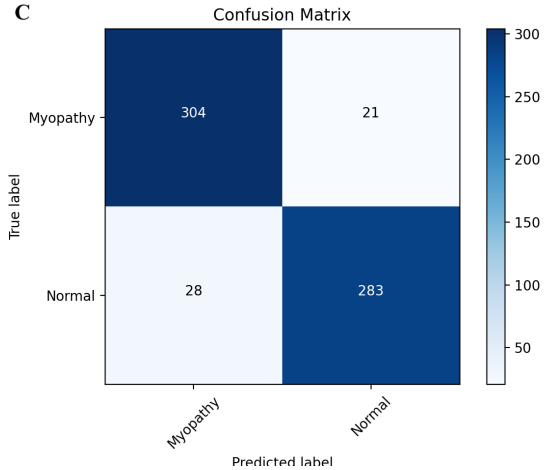
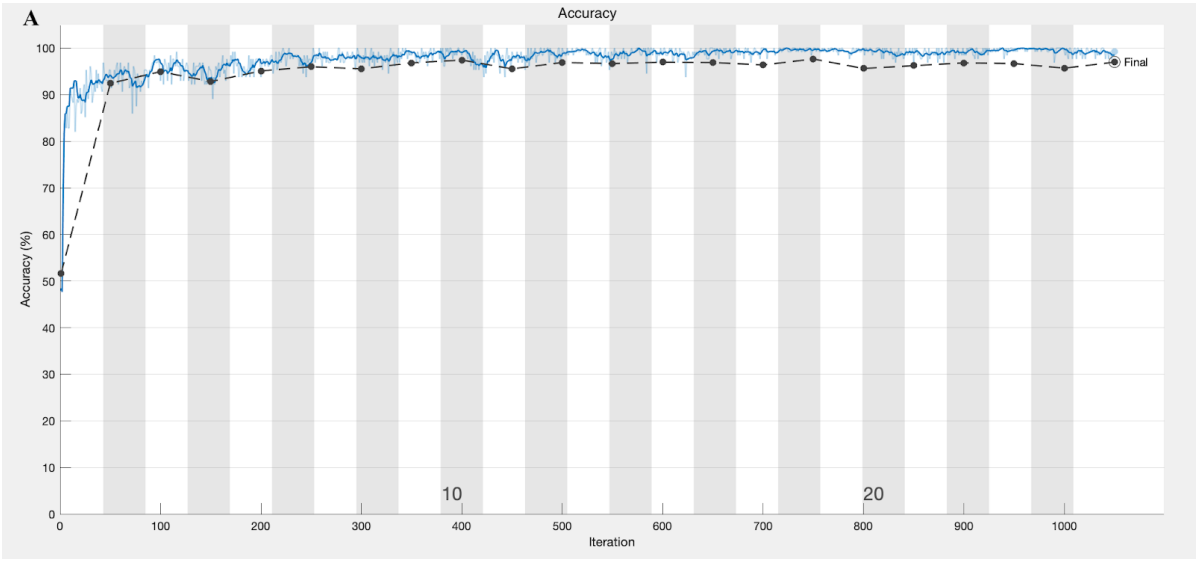
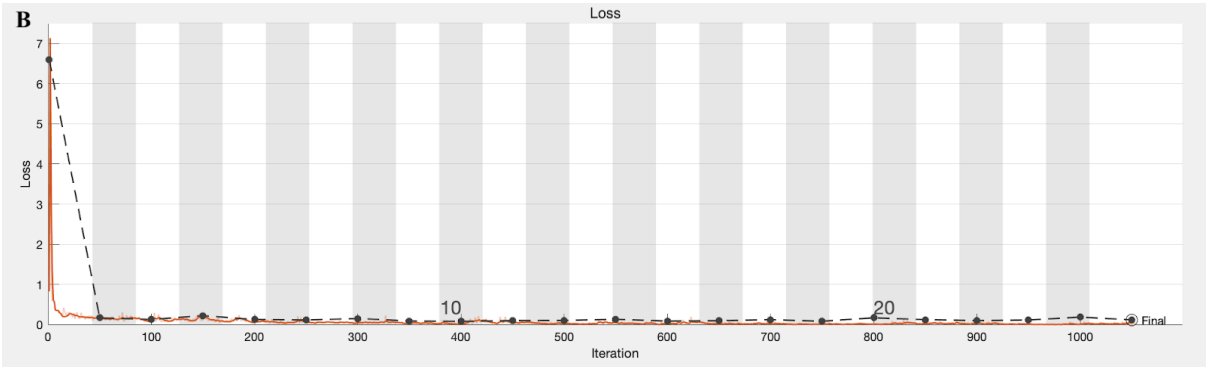


Figure 9.1


A
Accuracy
Accuracy (%)
Iteration
Final
10
20


B
Loss
Loss
Iteration
Final
10
20

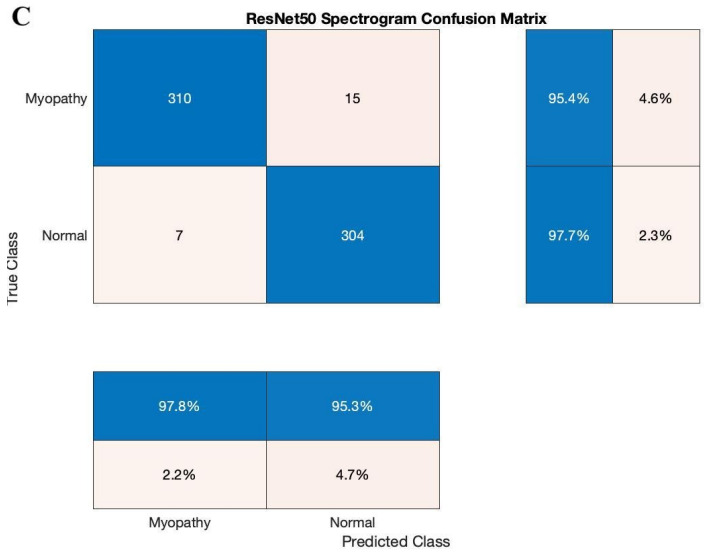
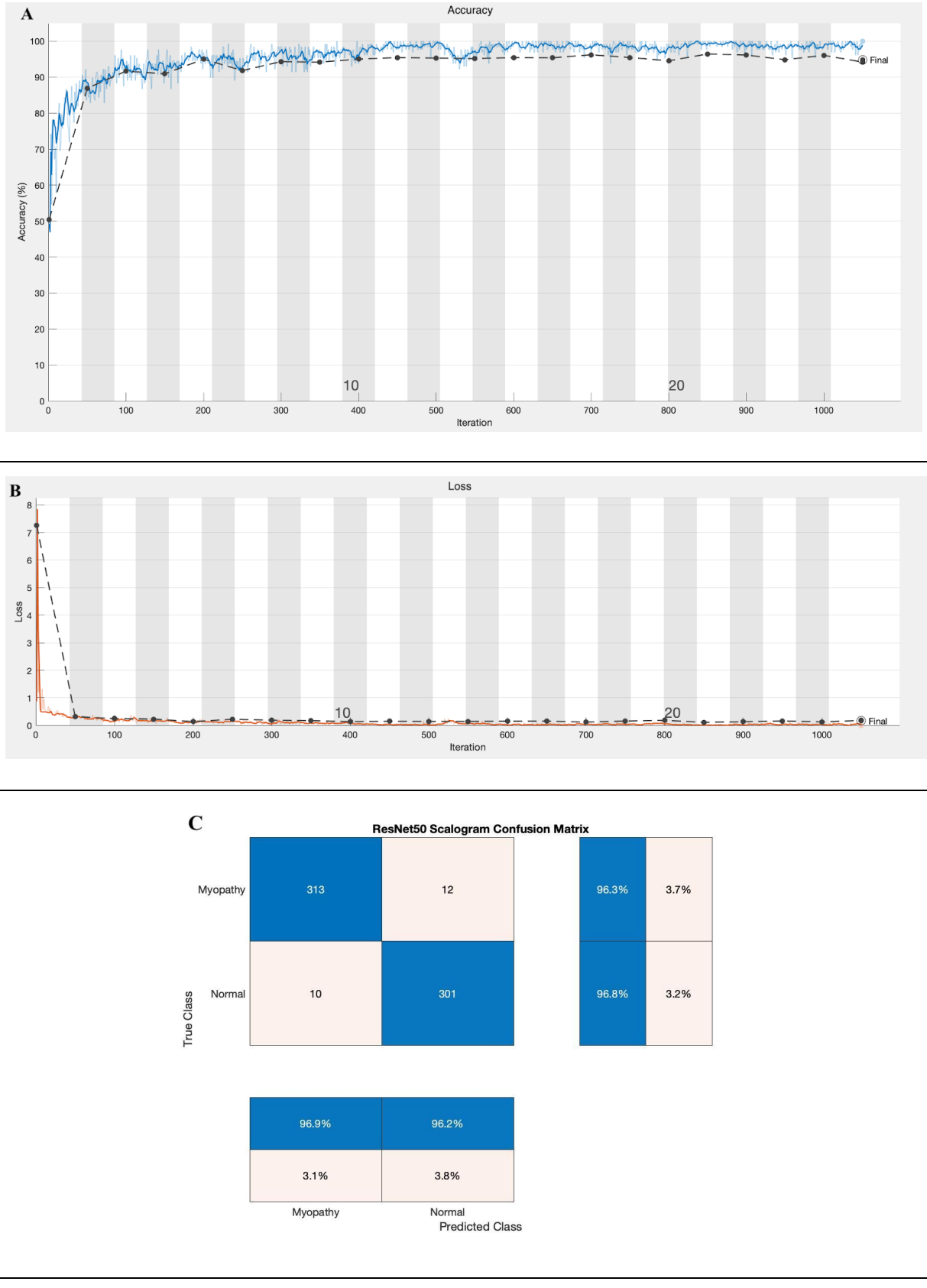

C
ResNet50 Spectrogram Confusion Matrix
Myopathy
Normal
True Class
310
15
7
304
95.4%
4.6%
97.7%
2.3%
97.8%
95.3%
2.2%
4.7%
Myopathy
Normal
Predicted Class

Figure 9.2


A
Accuracy
Accuracy (%)
Iteration
Final
10
20
B
Loss
Loss
Iteration
Final
10
20
C
ResNet50 Scalogram Confusion Matrix
Myopathy
Normal
True Class
313
12
10
301
96.3%
3.7%
96.8%
3.2%
96.9%
96.2%
3.1%
3.8%
Myopathy
Normal
Predicted Class

Figures 7 and 8. The accuracy (A), loss (B), and confusion matrix (C) of the VGG3 spectrogram (7.1) and scalogram (7.2) neural network and the VGG16 spectrogram (8.1) and scalogram (8.2) transfer neural network [figure 8]

Figure 9. The accuracy (A), loss (B), confusion matrix (C) for the ResNet50 spectrogram (9.1) and scalogram (9.2) neural networks.

Table 2. Comparison of the accuracies in classification between normal and myopathy EMG signals

Accuracy (%)	**Method**	**Classification**	**Study**	**Year Published**
96.75	Wave Decomposition and BP neural network	Myopathy Normal	[18]	2013
96.57	ResNet50 neural network fed spectrogram representations	Myopathy Normal	Swartwood (this paper)	unpublished
92.50	Mel-frequency cepstral coefficient (MFCC) on motor unit action potentials (MUAPS)	Myopathy Normal	[6]	2014
90.00	Wavelet Neural Network using AR method for EMG representation	Myopathy Normal Neurogenic	[23]	2006
73.33	Time Domain and Wavelet Decomposition	Myopathy Normal	[10]	2007

Discussion and Conclusion

Data Analysis

The ResNet50 neural network achieved the highest accuracy for both spectrogram (96.57%) and scalogram (96.55%). This is most likely due to the use of transfer learning and the fact that ResNet50 uses identity mapping [11], while both the VGG3 and VGG16 neural networks are convolutional neural networks.

Spectrogram representations were more accurate for the VGG3 network while scalogram representations worked better for the VGG16 transfer network. The regular VGG3 model (94.96% spectrogram, 88.36% scalogram) performed better than the VGG16 model (93.08% spectrogram, 92.30% scalogram). Between spectrogram and scalogram representations, the two are very similar in accuracy, which parallel the data in the first study [22]. Spectrogram representations tend to slightly outperform scalogram representation in terms of test accuracy.

This investigation's ResNet50 neural network accuracy (96.57%) was similar to the accuracy of the 2017 study distinguishing between ALS and normal signals (96.80%), which was the study that inspired this investigation's methodology [22]. These similar results indicate that the current study was appropriately conducted using high standards that are comparable to the published literature.

The highest accuracy model from this study, the ResNet50 spectrogram trained neural network (96.57% accuracy), is compared to previous studies in Table 2. The accuracy of the ResNet50 model in this investigation is higher compared to the accuracies reported in previous studies (Table 3) [6, 10, 23]. The 2013 study [18] that showed higher accuracy than ResNet50 used wave decomposition and a BP neural network to obtain a 96.75% accuracy. However, the difference between the 2013 study and this investigation's accuracy is very small (0.18%).

Additionally, the 2013 study [18] only used 20 myopathy and 20 normal images from a different source to test its data, creating a 60-40 train-test data split. This means that 40% of the images were checked to create this accuracy, which is only 16 images. This sample size is too small to give sufficient evidence for the accuracy and limits its general relevance. In contrast, the current investigation used 636 signal sections to confirm its accuracy, which makes its accuracy much more reliable for applicable diagnosis. This study's high accuracy and larger sample size compared to other studies make it one of the most reliable studies classifying between myopathy and normal EMG signals.

This investigation's ResNet50 neural network misdiagnosed with an error of 3.43%, which is within the manually-read imaging diagnostic error rate ranging from 3% to 5% [9]. Since this is within the range of probable error, the neural network cannot be deemed as either more or less accurate. However, it does indicate that this method is as effective as current standards. This makes it a viable tool for diagnosing even compared to specialists and further supports its use, either outright as a diagnostic tool or as a supplement to confirm the specialist's reading.

Cost Analysis

The eventual goal of this study and other similar studies is to create an automated diagnosis system that can distinguish between all EMG detectable conditions with a higher accuracy than humans in order to reduce human errors and the cost of these tests significantly. For patients without insurance, an EMG typically costs between $150 and $500 per extremity, depending on the health care provider [5]. Averaging these values yields an EMG price of about

$300. That means that each EMG signal that is misdiagnosed wastes $300. This happens 3-5% usually for most imaging tests [9]. Using automated diagnosis once it has a higher accuracy than specialist's diagnosis, or using the two in conjunction could reduce this misdiagnosis rate and save money from wasted EMG signals. On top of this, money from lawsuits that could arise from misdiagnosis could also be saved. The average settlement value for a medical malpractice lawsuit in the U.S. is somewhere between $300,000 to $380,000 [25]. Even without a lawsuit, misdiagnosis causes intangible damage, causing a patient to suffer unnecessarily.

Additionally, patients may need to schedule a follow-up visit with a primary-care doctor to discuss the results of an EMG test [5]. The average price of an office visit for an uninsured patient is $199 [5]. With fully automated diagnosis of EMG signals, this follow up appointment would prove unnecessary more often because automate diagnosis could return near instant results, saving this $199 for nearly each test. Fully automated diagnosis could also save the specialist time from having to diagnose the signal, which equates to a certain intangible amount of money.

Error Analysis

There were a few potential sources of error in the network. When splitting the EMG signal into various parts, it is possible that some of these sections did not have distinguishable features in them, leading to poorer training and therefore a lower network accuracy.

There was also slight overfitting in networks, as depicted in the accuracy and loss graphs of figures 8, 9, and 10. Since the model was training from a relatively small pool of data, consisting of only 215 EMG signals, after some epochs the model reached nearly 100% train accuracy. Overfitting happens when the neural network begins to memorize the training data.

Slight overfitting is normal, but excessive overfitting lowers network accuracy. Although the training was stopped early to prevent excessive overfitting, it is possible that overfitting slightly lowered validation and test accuracy.

Another possible source of error is the random splitting of the training, validation, and test data. These splits can have a random bias where some images that are ‘easier’ to read than others are sorted into different directories. This can end up skewing the data. Although this is unlikely (due to the similarities in validation and test percent accuracy), it could have a slight influence on the accuracy.

There were some technological limitations to the experiment. It would take several hours to a few days to train each network, which prevented further experimentation with various training options. It is very likely there are more network parameters like weight decay and other transfer learning models that could obtain higher accuracies on the data. This also prevented the usage of other testing methods, such as k-fold validation.

Conclusion

It was hypothesized that after a transfer neural network is trained on time frequency representations of EMG signals, such as spectrogram and scalogram representations, the neural network would be able to accurately (90%+) classify between normal and myopathy EMG signals. This was supported because after training neural networks on time frequency representations, the ResNet50 transfer model achieved a 96.57% accuracy when classifying between normal and myopathy spectrogram representations of EMG signals. The obtained results are similar to the 2017 study [22] that inspired the methodology of this investigation. This

confirms the value in performing analyzing time frequency representations of the images and supports the usage of deep learning as a medical diagnosis system.

Application

The results of this investigation contribute to the current research on the automated diagnosis of disease with its high accuracy classification between myopathy and normal EMG signals. The rising prominence of neural networks with their technological advancements is making automated diagnosis turn from dream to reality. Not only will normal and myopathy EMG signals be diagnosed automatically, but the entire medical field will transition to automated diagnosis. Eventually, completely automated medical diagnosis for most diseases reshape the medical field by offering cheap, effective diagnosis. With higher accuracy and more time efficiency, automated medical diagnosis can save an abundant amount of money, but even more importantly, it can save lives.

Future Work

Future studies can thoroughly investigate the exact features the network is extracting from these representations. Also, future studies can be conducted more accurately by collecting more EMG data from patients to test. Signals can be extracted from different muscle types and can be taken at different sampling frequencies to increase the range of data. A neural network could also distinguish more neuromuscular conditions to broaden the range of automated EMG diagnosed diseases, in the hopes that eventually machine learning can diagnose almost all EMG-related conditions**.**

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